

EXHIBIT F

The Prediction of Individual Probabilities of Brand Choice

DAVID J. REIBSTEIN*

This paper investigates three alternative methods for estimating individual probabilities of brand choice: a multi-attribute attitude model, a dollar-metric model, and a constant sum scale. These approaches are compared to actual choice behavior in a controlled experimental setting, with the constant sum scale being the dominant method.

In recent years, researchers have used individual probabilities of brand choice to develop stochastic marketing models (Bass 1974; Blattberg and Sen 1976; Dodson 1975; Ehrenberg 1972; Herniter 1973; Jeuland 1976; Massy, Montgomery, and Morrison 1970; Reibstein 1975). Based on the premise that for each individual there exists a vector of probabilities of choice ($\theta = \theta_1, \theta_2, \dots, \theta_n$) for each of the n brands in a given choice set, numerous models of brand switching and brand penetration have been developed. Such models can be extremely useful in describing both competitive intensity and market opportunities. Much of the controversy has focused on the distribution of these probability vectors across the population and the method for aggregating them to form descriptions of market behavior.

This paper is not intended to be still another attempt, assuming a new distributional form, to model brand switching behavior. Instead, the focus of this research is on the core element of the problem—the individual probability vectors. One way to determine an individual's actual probability vector is to gather purchase history panel data and compute the relative frequency of purchase for each of the brands; but this process is both time consuming and costly because one must acquire a large number of trials to derive reasonably accurate estimates of the probabilities. For low cost, frequently purchased items this wait may not be a problem, but for major durables, such as household appliances, the wait is liable to be unreasonably long. Further, over an extended period of time, new brands may enter the market, thus altering the probability vector.

* David J. Reibstein is Assistant Professor of Marketing, Graduate School of Business Administration, Harvard University, Boston, MA 02163. The author wishes to thank Professor Frank M. Bass for his valuable guidance.

Thus, there is a need for an expedient, relatively low cost method for determining individual probability vectors. The central issue addressed in this paper is the appropriate paper and pencil measure of these probabilities. To investigate this issue, it is necessary to consider some of the dimensions that lead to choice.

Behavior is usually preceded by behavioral intention. Behavioral intent presumably follows from brand preference. In turn, preferences are results of attitudes the consumer has about a variety of dimensions relevant to the product category (see Exhibit).

Measurements can be taken at any stage along this sequence. The closer the construct is to actual behavior, the more accurate it should be in predicting actual behavior. Unfortunately, the further away from behavior along this continuum, the more the information allows us to understand the choice itself. With such an understanding, it becomes clearer how a manager might manipulate the product mix to increase the likelihood of consumer choice (Pessemier 1977).

As we move along the continuum away from behavior, the question becomes how much deterioration there is in the information about actual choice probabilities. To investigate this question, each construct must be measured and compared to actual behavior.

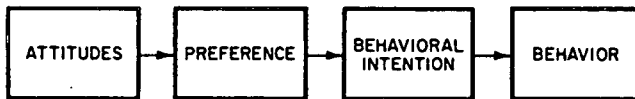
MEASURES

Behavioral Intention

A simple and direct approach to determining behavioral intention is to gather constant sum scale values. This procedure calls for the respondent to divide a fixed number of points over all brands in the choice set proportional to the percent of time the respondent intends to purchase each brand. Thus, if the number of points is set at 100, subjects are asked to estimate the percent of time they would normally purchase each brand, given a particular choice set. In other words, respondents directly provide their probability vector.

EXHIBIT

CONSTRUCTS LEADING TO CHOICE



This procedure was originally proposed by Metfessel (1947). However, applications in a brand choice setting are limited. Studies by Byrnes (1964), Ferber and Piskie (1965), Juster (1966), and Granbois and Summers (1975) have all investigated the predictive ability of subjective purchase probabilities, which are quite similar to constant sums. In each case, the study dealt with one purchase occasion and the analysis was performed across individuals. The intent of these studies was to predict whether a purchase would be made in a product class, not to ascertain individual probability vectors. Although their studies indicated that individuals can respond to direct questions about probabilities of purchase, and the probabilities are accurate over the population, these studies were not concerned with determining the ability of individuals to predict brands. This study empirically shows the relationship between behavioral intention and actual choice behavior on an individual basis.

Preference

A direct and commonly used approach to measuring preference is to obtain a preference ranking. Although this approach produces an ordinal preference, it does not reveal the strength of preference for the alternative choices. Pessemier (1960) developed a simple alternative method, the dollar-metric method, which captures both order and strength of preference. The procedure is rooted in the paired comparison perceptual models of mathematical psychology (Torgerson 1958).

This procedure has also been used for developing probabilities of brand choice (Pessemier, Burger, Teach, and Tigert 1971). In an external validity test, Nevin (1974) obtained dollar-metric values for two product categories—cola and coffee. The analysis was across the entire sample population; that is, he predicted changes in the brands' market shares in response to price changes in simulated shopping trips. Nevin concluded that the model "... generated reasonably valid estimates of consumers' reactions to actual price changes for the cola product category" (p. 266). He found contrary results for coffee. As choice behavior over a large number of trials was not gathered, no effort was made to evaluate external validity on an individual basis.

Attitudes

The measure of attitudes employed herein is commonly referred to as the multi-attribute attitude model, a linear weighted additive compensatory model. This

approach provides not only an ordering of brands, but an attitudinal score that reflects relative levels. A large portion of the research using this model has been concerned with testing various model forms (Wilkie and Pessemier 1973). In the majority of cases, the test of alternative model forms has been a measure of the correlation between the model's attitude score and stated preference rankings. It has generally been accepted that the model (in all of its forms) produces reasonable scale values for each of the brands.

Many efforts have been directed to predicting choice behavior from the multi-attribute attitude model (Sheth 1970; Bass, Pessemier, and Lehmann 1972; Lutz and Howard 1971; Ginter 1972; Winter 1972; Heeler, Kearney, and Mehaffey 1973; Kraft, Granbois, and Summers 1973). The majority of these studies performed an aggregate analysis over all subjects for a single purchase occasion. Results have been mixed, probably because many factors may intercede before the actual choice is made. How much information is contained in attitudinal measures about actual choice behavior for an individual over several purchases remains to be ascertained.

Conversion to Probabilities of Brand Choice

The constant sum scale provides a direct measure of an individual's probability of brand choice. In contrast, the dollar-metric model and the multi-attribute model provide *scale values* of preference and attitudes, respectively. The question becomes: how does one convert these scale values into relative probabilities of choice?

A method designed for the conversion of scale values for a set of brands into the probabilities of choice is Luce's Choice Axiom (Luce 1959). Based on the choice axiom, the probability of an individual (k) selecting a specific brand (i) from a choice set (T) can be expressed strictly as a function of the scale values of the brands in the choice set (Coombs, Dawes, and Tversky 1970) as,

$$P_k(i; T) = \frac{S_k(i)}{\sum_{j \in T} S_k(j)}, \quad (1)$$

where $S_k(i)$ is the scale value for individual k of brand i .

The thrust of the choice axiom is to maintain the ratio between all pairs of brands. Thus, for example, if choice set T has Brands A and B , with corresponding scale values for individual k of $S_k(A) = 2$ and $S_k(B) = 8$, the probability that Brand B will be chosen will always be four times the probability of Brand A being chosen, regardless of which other brands are in the choice set. (This is referred to as the constant ratio rule.) If no other brands are in the choice set, then $P_k(A; T) = 0.20$ and $P_k(B; T) = 0.80$.

If there is an additional brand C , with a scale value of 10, $S_k(C) = 10$, then the corresponding probabilities of choice would be $P_k(A; T) = 0.10$, $P_k(B; T) = 0.40$, and $P_k(C; T) = 0.50$.

If these probabilities do not correspond with the actual probabilities of choice, the conclusion must be either that the scale values are not good measures of the likelihood of choice (a principal focus of this study) or that the assumption of Luce's Choice Axiom of ratio scaled values is violated. This latter assumption does not preclude the models from providing good ordinal scales of choice, but only in these relative values. That is, it is possible that *C* is the most frequently chosen brand followed by *B* and *A*, but that *C* is not chosen five times as frequently as *A*, *B* is not chosen four times as frequently as *A*, and *C* is not chosen 25 percent more frequently than *B*. Thus, the reasonableness of the choice probabilities derived through Luce's Choice Axiom depends on the reasonableness of the scale values provided, and the "ratio-ness" of the data.

A second assumption in Luce's Choice Axiom, and common in most choice theories, is the assumption of independence among alternatives. Clearly, Luce's Choice Axiom is based on relative scales and, through the constant ratio rule, maintains that the brands' relative levels are independent of other brands in the choice set.

A third assumption is that the scale values for all brands are non-negative; otherwise the model would produce negative probabilities for the brands associated with negative scale values and possibly probabilities greater than one for others.

The reasonableness of the choice probabilities depends on the reasonableness of the scale values used in the model. As both the dollar-metric model and the multi-attribute attitude model provide positive scale values for each of the brands in the choice set, and these scale values have generally been accepted as relatively accurate representations of preference, they can be used to derive probabilities of choice in this study.

The scale values obtained from the dollar-metric model can be directly inserted into Equation 1 to derive probabilities of brand choice (Pessemier et al. 1971). However, the multi-attribute model provides the largest scale values for the least preferred brands, or most distant from the ideal.¹ Thus, if the scales are reversed with regard to desired order, it is necessary to alter

the scale values while still maintaining the same ratio between brands. That is, if the scale values for Brands *x* and *y* are such that $S(x) < S(y)$, yet the desired interpretation is that Brand *x* has a higher probability of choice than Brand *y*, it is necessary to transform the data while not altering the ratio between the scale values of the brands.

For example, if the corresponding scale values for Brands *x*, *y*, and *z* are {2,4,6}, respectively, and the interpretation of the scale value is that lower values imply a higher probability of choice, then it is desirable to maintain the ratio between brands such that,

$$\frac{P(x; T)}{P(y; T)} = 2, \quad \frac{P(x; T)}{P(z; T)} = 3, \quad \text{and} \quad \frac{P(y; T)}{P(x; T)} = 1.5.$$

The direct application of Luce's Choice Axiom in Equation 1 provides $P(x; T) = 1/6$, $P(y; T) = 1/3$, and $P(z; T) = 1/2$, which is opposite from the desired interpretation of the scale values.

Thus, it is necessary to reformulate the model while maintaining the desired ratios. As shown in the Appendix, the resulting model is

$$P(i; T) = \frac{1}{A_{ik} [\sum_{j \in T} (1/A_{jk})]} \quad (3)$$

Returning to the illustration just given,

$$P(x; T) = \frac{1}{2(1/2 + 1/4 = 1/6)} = \frac{1}{2(11/12)} = 6/11$$

$$P(y; T) = \frac{1}{4(11/12)} = 3/11$$

$$P(z; T) = \frac{1}{6(11/12)} = 2/11,$$

and thus the desired ratios are obtained. It is also important to notice that we must have

$$\sum_{j \in T} P(j; T) = 1. \quad (4)$$

Hence, the resulting attitude scores, derived from the multi-attribute model could be directly inserted into Equation 3 to obtain probabilities of brand choice.

In this study, preferences and intentions were measured in a survey, and actual choice behavior was observed over a number of trials. The predictive ability of each construct probability vector was tested on an individual basis.

DATA

A simulated supermarket was constructed at Purdue University in the fall of 1974. One hundred thirty-eight subjects, students and secretaries, were paid to attend daily for six weeks (a total of thirty trials), during which they would pay for a soft drink of their choice from a set of six most popular brands. As over 32 percent of soft drink consumers in this country are members of the 18- to-24-year age category,² the selection of

² Data taken from Target Group Index, 1974.

¹ The multi-attribute attitude model in its most general form (Wilkie and Pessemier 1973) is

$$S(i) = A_{ik} = \sum_j (V_{jk}[B_{ijk} - I_{jk}]) \quad (2)$$

where A_{ik} = the attitude score towards brand *i* by individual *k*, V_{jk} = the importance weight of attribute *j* for individual *k*, B_{ijk} = the belief about the level of attribute *j* contained in brand *i* by individual *k*, I_{jk} = the ideal level of attribute *j* for individual *k*. A variety of forms of the general model were attempted—with and without the stated importance weights, with and without the inclusion of an ideal point, and with a Minkowski metric of one or two. The model employed in this study, Equation 2, resulted in the highest Spearman rho rank correlation of all the model forms.

TABLE 1

NUMBER OF INDIVIDUALS FOR WHICH THE CONSTRUCT PRODUCED THE HIGHEST CORRELATION WITH THE ACTUAL RELATIVE FREQUENCY

Subjects	BI ^a	PREF ^b	ATT ^c
Group 1			
All prices held constant and equal	37	12	1
Group 2			
Prices constant but different	25	14	4
Group 3			
Prices varied and different	28	14	3
Total	90	40	8

^a Constant Sum Scale Model.

^b Dollar Metric Model.

^c Multi-Attribute Attitude Model.

student subjects did not seem totally inappropriate. From the 30 brand selections it was possible to derive a vector of relative frequencies of brand choice for each individual.

There were three experimental groups—two that had varying prices and a third that had stable and equal prices among all brands. On one occasion the participants completed a questionnaire with all the information needed for the three constructs.³

RESULTS

For each individual in the experiment, four probability vectors were obtained—the relative frequencies of brand choice exhibited in the experiment and the three construct probability vectors. If the construct probability vector is a good approximation of the actual relative frequency vector, there should be a high positive correlation between the two; the better the predictive model, the higher should be the correlation. Correlations could be obtained in several different ways—by individuals across brands, by brands across individuals, and across individuals and brands. Correlations derived by individuals across brands would be most appropriate for determining the information contained in probabilities of brand choice, on a subject-by-subject basis.

When correlations are obtained for proportions, it is useful to use the following transformation

$$\bar{\theta}_i = 2 \arcsin \sqrt{\bar{\theta}_i} \quad (5)$$

to stabilize the variances (Winer 1971, p. 700; Torgereson 1958, p. 203). The results after the transformation are only slightly different from correlations derived on the raw data.

For 65 percent of the subjects, the behavioral intention measure had the highest correlation with the actual relative frequencies; for 29 percent the preference measure dominated; and for only 6 percent the multi-attribute attitude model prevailed (Table 1). For some

³ For details of the experiment, see Reibstein (1975).

TABLE 2

AVERAGE CORRELATION (AND STANDARD DEVIATION) BETWEEN CONSTRUCT PROBABILITY VECTOR AND ACTUAL RELATIVE FREQUENCIES

Subjects	BI ^a	PREF ^b	ATT ^c
Group 1			
All prices held constant and equal	.78 (.24)	.64 (.27)	.54 (.45)
Group 2			
Prices constant but different	.60 (.45)	.56 (.32)	.52 (.44)
Group 3			
Prices varied and different	.72 (.36)	.59 (.36)	.43 (.48)

^a Constant Sum Scale Method.

^b Dollar Metric Model.

^c Multi-Attribute Attitude Model.

individuals, all three measures produced correlations that were significantly different from zero, while for other individuals only some, and in some cases, none of the models produced significant correlations. Table 2 shows the correlations for each model averaged across all the subjects.

For the constant sum scale, the predictions were significantly more accurate ($\alpha < 0.01$) than for the dollar-metric model and the multi-attribute model. The average correlations obtained from the dollar-metric model were significantly greater than the average correlations derived from the multi-attribute attitude model for Group 1 ($\alpha < 0.05$) and Group 3 ($\alpha < 0.01$).⁴

A similar measure is the distance, or squared error, between the derived probability of choice vectors and the exhibited probabilities of brand choice. The Figure shows the distances for each of the three constructs, averaged across the entire sample. Again, it can be seen that there is a considerable loss of information about brand choice as we move away from the behavioral intention measure.

In predicting the brand most frequently chosen by an individual, similar results were obtained. The multi-attribute model predicted the brand most frequently chosen for only 22 percent of the subjects. A purely random model would produce correct results for 16

⁴ Morrison (1972) has shown that there is an upper limit, less than or equal to one, on correlations between predictions of probabilities and binary outcomes, and Gaver and Rabinovitch (1975) have extended this finding to the multivariate case. In other words, the correlations between the predicted preference vectors and the actual relative frequencies are even more impressive than their absolute levels would indicate. The predicted probabilities are continuous but the actual relative frequencies have a lattice outcome, and hence, the level of linear association is constrained. This fact is relevant if the major concern is the absolute level of correlation obtained, but it is not relevant in comparisons of correlations derived from different predictive models and the actual relative frequencies, as is the interest in this section. The upper bound provides information on the room for improvement from even better predictive models.

INDIVIDUAL PROBABILITIES OF BRAND CHOICE

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percent of the subjects. The constant sum scale and the dollar-metric model predicted the most frequently chosen brand for 65 percent and 52 percent of the subjects, respectively. When attitude scores were correlated with stated preference rankings, the results obtained were similar to those achieved in previous applications of the model. The Spearman Rho rank correlation was 0.52, within the range found in other studies.

CONCLUSION

In this study the choice process was highly constrained so that minimal factors could intervene between attitudes and choice; that is, there were no stock-outs, special promotions, unusual displays, etc. Even in this controlled setting, there was a clear gap between attitudes and behavior. It can only be expected that this gap would widen in a less constricted environment.

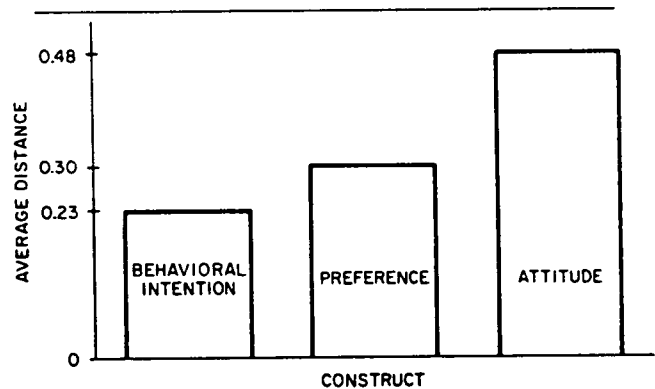
On the other hand, the evidence indicates that behavioral intention, as measured by a constant sum scale, can predict the probability of brand choice on an individual basis. There apparently is a loss of information about brand choice when we digress to a measure of preference using the dollar-metric model. This conclusion holds for subjects who have a small number of dominant brands, as well as for those whose probabilities of brand choice are dispersed across a large number of brands.

As we progress even further from the measure of behavior, the deterioration of information about choice behavior is substantial. The results indicate that for the overwhelming majority of the subjects, the probabilities of brand choice based on the multi-attribute attitude model are not closely related to the actual choice exhibited in the experiment. From this, two conclusions are possible: the probabilities of brand choice are not highly related to attitudes as measured by the multi-attribute attitude model; or it is inappropriate to apply Luce's Choice Axiom to the attitudinal data. Given that the scale values derived from the multi-attribute attitude model are all positive, this latter contention could only be true if the choices were not independent or if the scale values were not ratio scaled. It is clearly possible that the choices were not independent, but this would also be true for the dollar-metric model applied to the same choice set, which performed substantially better.

If, on the other hand, the difficulty lies in the assumption of ratio-scaled data, we have again reached the conclusion that the multi-attribute attitude model does not provide good *relative* measures that would be related to brand choice. This finding would caution against drawing a hasty link between attitudes and behavior.

Most significant is the apparent information about brand choice that is captured by the constant sum scale. If additional studies for a variety of products and contexts reveal similar results for the constant sum scale,

FIGURE
AVERAGE DISTANCE BETWEEN ACTUAL RELATIVE
FREQUENCIES AND DERIVED PROBABILITY OF
BRAND CHOICE



it may be possible in future research for this paper and pencil measure to be used as a surrogate for actual choice.

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APPENDIX

Reversal of Scale for Luce's Choice Axiom

Luce's Choice Axiom assumes that the higher the scale value for a choice, the greater the likelihood of its being chosen. Stated another way, the more positive the feeling for an object, the greater the scale value to be assigned. However, if the scales are reversed with regard to desired order, it is necessary to alter the scale values while still maintaining the same ratio between brands. That is, if Brand x has a scale value $S(x)$ and the scale value for y is $S(y)$, and $S(x) < S(y)$, yet the desired interpretation is that Brand x has a higher probability of choice than Brand y , it is necessary to transform the data to achieve the inverse ratio between the scale values of the brands.

Such a transformation would allow the application of Luce's Choice Axiom:

$$P_k(x; T) = \frac{S_k(x)}{\sum_{y \in T} S_k(y)} \quad (A-1)$$

The reformulation of the model with the inverse ratios is:

$$P_k(x; T) = \frac{\frac{S(x)}{\sum_{y \in T} S(y)}}{\sum_{y \in T} \frac{S(y)}{S(x)}} \quad (A-2)$$

As $\sum_{y \in T} S(y)$ is a constant, Equation A-2 can be written as,

$$P(x; T) = \frac{[\sum_{y \in T} S(y)]/S(x)}{[\sum_{y \in T} S(y)][\sum_{y \in T} 1/S(y)]} \quad (\text{A-3})$$

which

$$= \frac{1}{S(x)[\sum_{y \in T} 1/S(y)]} \quad (\text{A-4})$$

Thus, if the scale values are derived from the multi-attribute attitude model (2), the choice axiom (1) must be converted to Equation A-4, and the corresponding attitude scores would serve as the scale values. Hence, in multi-attribute notation, Equation A-4 becomes

$$P_k(i; T) = \frac{1}{A_{ik}[\sum_{j \in T} 1/A_{jk}]} \quad (\text{A-5})$$

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